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Spatial Dimensions of Stated Preference Valuation in Environmental and Resource Economics: Methods, Trends and Challenges

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Abstract: An expanding literature addresses spatial dimensions related to the elicitation, estimation, interpretation and aggregation of stated preference (SP) welfare measures. Recognizing the relevance of spatial dimensions for SP welfare analysis and the breadth of associated scholarly work, this article reviews the primary methods, findings, controversies and frontiers in this important area of contemporary research. This review is grounded in a typology that characterizes analytical methods based on theoretical foundations and the type of statistical modelling applied. The resulting interpretive appraisal seeks to (1) summarize and contrast different theoretical arguments and points of departure within the spatial SP literature, (2) synthesize findings, insights and methods from the literature to promote a more holistic perspective on the treatment of spatial dimensions within SP welfare analysis, (3) evaluate and reconcile divergent approaches in terms of theoretical grounding, ability to identify relevant empirical effects, and relevance for SP valuation, and (4) discuss outstanding questions and research frontiers.

Keywords: Discrete Choice Experiments; Contingent Valuation; Spatial Heterogeneity; Distance Decay; Spatial Dependence; Spatial Autocorrelation; Non-Market Goods; Ecosystem Services; Willingness to Pay; Willingness to Accept

Abbreviations: SP: Stated Preference; WTP: Willingness to pay; WTA: Willingness to accept

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1. Introduction

Most issues studied by environmental and resource economists involve spatial dimensions. The relevance of space for economic behavior, welfare and modeling is increasingly recognized across the literature.[1] Among the areas in which spatial dimensions play a central but sometimes underappreciated role is environmental stated preference (SP) welfare evaluation. An expanding literature addresses spatial issues related to the elicitation, estimation, interpretation and aggregation of stated preference welfare measures, including estimates of willingness to pay (WTP) and willingness to accept (WTA). Beginning with seminal work such as that of Sutherland and Walsh (1985), this literature demonstrates that WTP and WTA often depend on spatial aspects of the policy outcomes subject to valuation, the respondents whose values are elicited, and the information provided by SP questionnaires (De Valck and Rolfe 2018).

The welfare effects of virtually any environmental policy change may vary over space due to patterns that influence the supply and/or demand for affected goods and services (henceforth, "goods"). This has important implications; multiple authors have demonstrated or argued that the relevance of spatial patterns for policy evaluation can outweigh comparable effects of statistical and methodological issues that are often given greater attention in the literature (Smith 1993; Bateman et al. 2006; Campbell et al. 2009; Schaafsma et al. 2012; Johnston et al. 2016, 2017a). Among first-order concerns in this area, it is well established that benefit aggregation requires information on the spatial extent and

[1] Illustrative examples include Albers (1996), Albers et al. (2010), Ando et al. (1998), Ando and Baylis (2014), Bateman (2009), Bateman et al. (2002, 2006), Bell and Bockstael (2000), Bockstael (1996), Cameron (2006), Case (1991), Campbell et al. (2008, 2009), Duke et al. (2015), Irwin and Geoghegan (2001), Geoghegan et al. (1997), Johnston et al. (2002, 2017a, 2018), Johnston and Ramachandran (2014), Klaiber and Phaneuf (2010); Loomis (1996, 2000), Parsons and Hauber (1998), Paterson and Boyle (2002), Sanchirico and Wilen (1999, 2001), Schaafsma (2015), Smith and Wilen (2003), Sutherland and Walsh (1985), Swallow and Wear (1993); Termansen et al. (2013); Wilen (2007).

distribution of values (Smith 1993; Loomis 1996, 2000; Morrison 2002; Bateman et al. 2006). In addition, lack of attention to spatial patterns can lead to biased individual or mean welfare estimates, as well as an inability to measure aspects of welfare heterogeneity that are directly relevant to policy evaluation and a comprehensive understanding of public preferences (Loomis 1996, 2000; Bateman et al. 2006; Johnston et al. 2015, 2017a). Spatial dimensions are salient for both original SP studies and benefit transfer of study results (Morrison et al. 2002; Van Bueren and Bennett 2004; Morrison and Bennett 2004; Bateman et al. 2006, 2011; Schaafsma 2015; Johnston et al. 2016, 2017a, 2018).

Spatial dimensions of SP studies can be complex and require attention at all stages of research, from problem conceptualization to survey design to data analysis (Johnston et al. 2017b). Yet despite ongoing advances in economists' treatment of spatial dimensions, the SP literature as a whole still (arguably) underappreciates the relevance and complexity of these issues. The result is a frequent inability to estimate patterns that are, according to theory and economic intuition, relevant for welfare analysis.

Part of the challenge in moving towards a more comprehensive and cohesive treatment of spatial dimensions in SP studies is the lack of clear guidance from microeconomic theory, at least with regard to some of the ways in which space affects the value of environmental goods. Empirical patterns found in the literature often match theoretical expectations, although unequivocal theoretical expectations may not always exist. The lack of a cohesive and comprehensive theoretical foundation tends to encourage "proof of concept" or *ad hoc* treatments of spatial dimensions, with few consensus standards to guide research practices. Hence, despite an increasing number of individual studies characterizing spatial aspects of stated preferences in empirical terms, the literature still lacks a cohesive framework through which observed spatial patterns can be more consistently (and convincingly) modeled and understood.

Recognizing the relevance of spatial dimensions for SP welfare analysis and the breadth of associated scholarly work, this article characterizes the primary methods, findings and outstanding questions in this area of contemporary research.[2] This interpretive appraisal seeks to (1) summarize and contrast different theoretical arguments and points of departure, (2) synthesize findings, insights and methods to promote a more holistic perspective, (3) evaluate and reconcile divergent approaches in terms of theoretical grounding, ability to identify relevant empirical effects, and overall relevance for welfare estimation, and (4) discuss outstanding questions and research frontiers. The overarching aim is to promote consistent, valid and reliable treatment of spatial dimensions within SP studies.

2. Classifying the literature

To promote a coherent review of spatial dimensions within the empirical SP literature, we propose a conceptual, two-dimensional typology. This typology—or interpretive framework—is presented as a classification matrix that organizes the literature in terms of (1) the degree to which studies are motivated by microeconomic theory and (2) the methods used to characterize and model spatial dimensions. Classification focuses on differences in *model specification* and *data analysis*. It does not explicitly address other relevant topics mentioned in the SP literature such as benefit aggregation, or issues related to survey design and sampling as discussed in Section 5. Nonetheless, because the classification is grounded in general perspectives towards spatial phenomena, it can provide

[2] There is also a large literature addressing spatial issues in revealed preferences – these often involve distinct challenges and issues, and are only mentioned if directly relevant to SP analysis as well. Moreover, although contingent behavior modeling is often considered a form of SP analysis, we do not explicitly address the treatment of spatial dimensions within this work (e.g., see Broch et al. 2013; Lienhoop and Brouwer 2015).

a useful frame through which to view the entire literature.

2.1. Spatial dimensions of SP analysis: A classification matrix

Modeling of spatial dimensions in SP welfare analysis begins with a foundation in economic theory. Hence, an initial way to evaluate and distinguish studies is via their theoretical foundations. An appropriate theoretical model can provide *ex-ante* expectations that guide the specification of the bid or utility function and motivate specific hypotheses or model specifications related to spatial processes. For example, the travel behavior necessary to realize some types of use values implies that WTP values should often exhibit distance decay, *ceteris paribus*.

Yet spatial processes are complex and sometimes idiosyncratic, and economic theory does not provide direct insight into the full array of these processes. For example, theory offers limited guidance into whether and how non-use values might vary over space, and thus on the expected extent of the market (Hanley et al. 2003; Bateman et al. 2006; Johnston et al. 2015). Also, microeconomic theory often provides limited insight on the specifics of model specification—competing empirical specifications of a given phenomenon may all be consistent with theory. In some cases, it may also be useful to investigate spatial patterns with little or no *ex-ante* theoretical justification or constraints. Such exploratory, empirically driven approaches can reveal spatial patterns that have not (yet) been explained by theory.

The second distinguishing aspect of spatial welfare analysis is the type of empirical approach that is applied. Two broad categories can be identified in the spatial SP literature. The first common approach is the direct inclusion of *spatial variables* into the utility or bid function, where these variables represent observable spatial characteristics of the goods to be valued, the relevant context or market (including substitutes and complements), or survey respondents. For example, one might include a variable measuring the distance between a respondent and the good to be valued. Models of this type typically assume a particular structure for the deterministic (or observable) component of the utility or bid function that enables WTP/WTA to be estimated as a function of observable spatial variables. Estimation is typically implemented using traditional econometric methods for non-market valuation (e.g., discrete or continuous regression; Haab and MacConnell 2002; Train 2008).

Some spatial patterns, however, arise from spatial processes that cannot be readily captured in the deterministic component of regression models, leading to *spatial dependence or unobserved spatial heterogeneity* (Anselin 1988, 2001, 2010; Anselin and Getis 1992; LeSage and Pace 2009; Sener et al. 2011). For example, information transmission and resulting levels of awareness about (local) environmental problems may vary across space in a way that does not align well with administrative boundaries or other spatial variables and contribute to complex spatial patterns of WTP/WTA. In other cases, seemingly idiosyncratic but statistically significant spatial "hot" or "cold" spots may occur in WTP/WTA that cannot be explained by observable variables (Johnston and Ramachandran 2014). In cases such as these, spatial econometric or geo-statistical techniques may be necessary to avoid model misspecification and bias, or to reveal potentially relevant, yet unexpected spatial patterns in welfare. Related approaches can be used for spatial interpolation and prediction.

The resulting classification is conceptual and fuzzy—it is not always possible to unambiguously place a study into a single cell in the classification matrix shown in Table 1. For example, studies may make simultaneous use of both spatial variables and geo-statistical models. However, even a broad conceptual classification such as this one reveals relevant patterns. As discussed below, studies with strong structural grounding in microeconomic theory tend to rely on traditional econometric approaches with spatial variables, whereas exploratory studies (less grounded in theory) are more likely to model unobserved processes using spatial econometrics. Reconciling these two strands of inquiry in SP studies is an important area for future work.

With regard to the first dimension of the typology of spatial SP studies, we distinguish between a *strong link to economic theory*, a *weak link to economic theory* and *no link to economic theory*. This three-part classification is a discretization of the underlying continuous degree to which any empirical economic analysis may be informed by or grounded in theoretical constructs; valuation models can have varying degrees of formal theoretical foundation (Bergstrom and Taylor 2006). Approaches strongly linked to economic theory will typically determine model specifications using formal, structural derivations grounded in welfare theory. Those with weaker links may choose variables or specifications with consideration of theoretical expectations, but without strong structural links or derivations. Studies with no pre-established link to theory do not relate spatial processes to a specific *economic* theory or theoretical expectation (although they might have links to non-economic theory, as discussed below).[3] An *ex ante* theoretical foundation is not necessary for a study to provide useful information; studies with no link to theory can develop new explanations for detected spatial patterns, and in ideal cases can provide insights to motivate the development of new theory.

The second dimension of the typology distinguishes approaches that use observable *spatial variables* (and traditional econometrics) to investigate observed causes of spatial

[3] For example, evaluations of distance decay for use values are frequently grounded in either a strong or weak link to economic theory, given the direct link between site distance and access costs. In contrast, analyses of distance decay for non-use values have either weak or no link to theory, depending on the extent to which the analysts attempt to specify models based on a general theoretical motivation for observed patterns.

heterogeneity in welfare effects, and those that account for and model *spatial dependence* and *unobserved spatial heterogeneity*.[4] The latter type of approaches can, for example, be used to explore whether WTP for an environmental good tends to be more similar among households that are in closer proximity to each other, *ceteris paribus*, irrespective of (or in addition to) any effects related to other observable variables.

[Table 1 approx. here]

Grounded in this classification, the following subsections discuss key theoretical concepts underlying SP welfare analysis and empirical modeling approaches encountered within the literature.

2.2. Core theoretical foundations for spatial dimensions of stated preferences

Commonly discussed theoretical motivations for spatial welfare patterns include (1) distance decay, (2) spatially variable substitutes and complements, and (3) spatial dimensions of scope and diminishing marginal utility. These patterns may occur independently or jointly, and in some cases there are direct causal relationships among them.

Within the SP literature, *distance decay* implies that demand for a good decreases with distance, holding all else constant. Formally, demand for good Q is a function of own price p and distance d, such that $\mathrm{Q}(p, d)$ with $\frac{\partial Q}{\partial p} < 0$ and $\frac{\partial Q}{\partial d} \leq 0$. The literature provides several theoretical motivations for distance decay. For example, the price to visit a site increases with increasing distance through higher travel and time opportunity costs, such

[4] This categorization is similar, although not identical, to Anselin's (2010) discussion of spatial heterogeneity versus spatial dependence.

that distance is associated with higher effective prices to attain the good (Sutherland and Walsh 1985; Pate and Loomis 1997; Hanley et al. 2003; Bateman et al. 2006). The availability of substitutes often increases with distance, since the relevant consideration set expands (Pate and Loomis 1997; Rolfe et al. 2002; Hanley et al. 2003; Bateman et al. 2006). Search and information costs also tend to increase with distance, as people are often less familiar with distant sites and goods (Sutherland and Walsh 1985; Pate and Loomis 1997; Hanley et al. 2003). In addition, closer sites can be subject to increased levels of moral obligation and responsibility, *ceteris paribus* (Rolfe and Bennett 2002; Hanley et al. 2003; Bateman et al. 2005, 2006; Concu 2007; Johnston and Duke 2009). Arguments regarding travel and information costs and substitutes have strong microeconomic foundations. In contrast, the effect of knowledge, awareness of site quality and experience on demand is more an empirical than a theoretical question.[5] These arguments are salient for many types of location-specific use values. However, not all of them are directly applicable to use or non-use values for which site access is not necessary to realize benefits (Hanley et al. 2003; Bateman et al. 2006; Jørgensen et al. 2013; De Valck et al. 2017; Holland and Johnston 2017).

The availability of *substitutes and complements* provides some explanation of empirically determined distance decay effects for use and non-use values, but is also a relevant spatial dimension in its own right (Pate and Loomis 1997; Jørgensen et al. 2013; Nielsen et al. 2016; De Valck et al. 2017). Microeconomic theory suggests that the demand for a good depends on prices for substitutes p_s and complements p_c, i.e. $\mathrm{Q}(p, p_s, p_c)$, where

[5] For example, information on iconic assets (national parks) is widely transmitted and easily available through national media coverage, while obtaining information on local non-iconic assets may involve greater search cost. In such cases, one might expect non-use values to exhibit distance decay for non-iconic sites but not for iconic ones (or for distance decay gradients to differ between iconic and non-iconic sites).

$\frac{dQ}{dp_s} > 0$ and $\frac{dQ}{dp_c} < 0$. If the quantity (or availability) of substitutes and complements is exogenously determined ($\bar{q}_s$ and $\bar{q}_c$) then demand is given by $Q(p, \bar{q}_s, \bar{q}_c)$, where $\frac{dQ}{d\bar{q}_s} < 0$ and $\frac{dQ}{d\bar{q}_c} > 0$. Especially for local environmental goods, the availability and prices of substitutes and complements often vary spatially, for example in a site choice context.

Theoretical motivations related to *spatial dimensions of scope* address expectations that welfare effects should be sensitive to scope across various dimensions,[6] and that scope may vary over space. Effects of spatial scope are relevant to SP valuation in multiple ways. First, in some cases environmental goods may be arranged spatially so that the aggregate scope of change in these goods, for any given SP scenario, varies across space. Consider a program that restores wetlands in a given jurisdiction. A person's WTP for this change may be a function of the quantity of restored wetland area within a certain distance of their home, because they obtain a larger scope of improvement—more nearby restoration—if more restored wetlands are close to them. Similar spatial scope variations can occur if similar proportional improvements are made to regions that differ in terms of the baseline size of the areas that are improved (Spencer-Cotton et al. 2018). This is distinct from distance decay and diminishing marginal utility, as it suggests that the effective *quantity of the public good that would be realized within an SP scenario varies across space*. Variations such as these matter most in contexts where environmental quality changes apply to spatially-varying areas (Holland and Johnston 2017).

A second dimension of spatial scope relates to *diminishing marginal utility*. In this

[6] Expectations regarding scope sensitivity are context dependent. For environmental goods with unambiguously positive marginal utility, theory suggests that WTP "should be non-decreasing in the scope of environment quality or quantity of the natural resource allocation" (Whitehead 2016, p.17). However, there are a variety of reasons why valid SP results may not reveal scope sensitivity as defined above in practice, including diminishing (or negative) marginal utility, substitution effects, scenario framing, and various behavioral anomalies, among others (Heberlein et al. 2005; Whitehead 2016).

context, scope is related to the current endowment of a good provided within a SP scenario. Diminishing marginal utility implies that the utility increase from the consumption of one additional unit of a good x decreases with increasing consumption of that good, i.e. $\frac{\partial U}{\partial x} > 0$ and $\frac{\partial^2 U}{\partial x^2} < 0$, where U denotes utility. This implies that current endowments of an environmental good influence the marginal utility received from additional provision of that good, *ceteris paribus*. Current and future baseline endowments often vary spatially, leading to WTP variations associated with diminishing marginal utility.

2.3. Econometric approaches

Theory informs but does not determine econometric approaches for data analysis. Most of the theoretical concepts discussed above can be modeled via the inclusion of *spatial variables within traditional econometric models,* typically to investigate observed spatial heterogeneity or patterns in WTP/WTA. For example, simple distance decay may be modeled within traditional econometric specifications via the incorporation of distance variable(s) within bid or utility functions. Similar approaches may be used to incorporate potentially relevant and spatially varying features such as current endowments, scope, and substitutes and complements, among others. Observable factors such as these may be quantified as variables for direct inclusion within econometric models, e.g., as main effects or interactions within utility functions, or explanatory factors in mixing distributions or latent class membership functions. Within models such as these, the primary challenge is to identify variable definitions and model specifications that enable valid and reliable welfare estimation, as informed by microeconomic theory.[7]

[7] A commonly discussed example includes variable(s) used to measure distance. Various distance measures are available and may be appropriate in different circumstances. Additionally, any spatial variable may be subject

Regardless of the econometric approach that is applied, it may be unwieldy to include all spatial variables into a single-step regression. In such cases, authors have applied a two-step approach to estimate spatial effects (e.g., Campbell et al. 2008, 2009; Abildtrup et al. 2013; Johnston and Ramachandran 2014; Yao et al. 2014; Johnston et al. 2015; Czajkowski et al. 2017). In the first step, a non-spatial model allowing for unobserved preference heterogeneity (e.g., a mixed logit model) is estimated. Individual-level (conditional) parameters or WTP estimates are calculated from model results (Train 2008). In the second step, these individual-level estimates are regressed on one or several spatial variables, or used for other types of spatial analysis. There are advantages and disadvantages to the two-step approach. For example, where the two-step approach can enable a larger number of spatial variables to be included in the analysis without sacrificing degrees of freedom in the first-step model, all inferences in second-step models are conditional on the accuracy of the estimation of individual-level parameters, and should be interpreted accordingly (Abildtrup et al. 2013; Johnston et al. 2015). As spatial variables are often correlated with each other, including too many spatial variables in the model may also lead to multicollinearity. In such cases, factor analysis or principal component analysis may be used to reduce the number of explanatory variables – a common approach in the hedonic pricing literature (Fernandez et al. 2018).

The inclusion of spatial variables may also be useful even if not directly informed by theory. Spatial variables can increase the predictive power of a model and prevent omitted variables bias.[8] The inclusion of these variables can also help to explain "residual" spatial

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to measurement error (i.e. if the location of the respondent's home is not measured consistently or precisely; Moeltner et al. 2017) or correlated with other variables (e.g., distance and income).

[8] Omitted variable bias occurs when the omitted spatial variable is causally related to the dependent variable and correlated with at least one of the explanatory variables. The effect of the omitted variable is, to some extent, captured in the coefficient of the correlated explanatory variable. For example, assume that WTP for

effects when theory provides limited guidance (e.g., distance decay in non-use values).

Some spatial patterns, however, cannot be explained adequately using spatial variables or traditional econometric specifications—these include patterns that are inherently spatial, idiosyncratic from the perspective of economic theory, or not readily explainable using observable variables alone. For example, researchers might hypothesize that the preferences of individuals living closer to each other might have been shaped by shared experiences or through direct exchange among neighboring individuals. However, the specific reasons why the preferences of those individuals are similar remain unknown.[9] Such patterns characterized by *spatial dependence* and by *unobserved spatial heterogeneity* can lead to bias in traditional econometric results and require geo-statistical or spatial econometric techniques to be modeled (Anselin 1988; LeSage and Pace 2009). A common but not universal aspect of these techniques is the use of a spatial weights matrix to characterize spatial relationships among different observations, with weights typically defined using either distance bands or k-nearest neighbors (Anselin 1988, 2001; Johnston et al. 2015).

Spatial dependence implies a lack of independence among observations over space due to a functional relationship between effects across locations, such that estimated effects cluster. Such dependence can be inherent to the data or a result of omitted variables

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environmental amenities can be explained by employment status and whether a respondent lives in the southern part of the sample area (e.g. due to cultural differences). Assume further that more people have full time jobs in the southern part of the sample area than in the other areas. If we include only employment status as an explanatory variable, the coefficient for full time jobs would be biased as it would capture the effect of the omitted spatial variable (southern location). Although the spatial variable in this example does not have an economic meaning and may not be relevant to the research question, it should be included for unbiased estimation of other, economically relevant, variables.

[9] Underpinning such hypotheses about clustering of preferences is Tobler's first law of geography, stating that "everything is related to everything else, but near things are more related than distant things" (Tobler 1970). The law is based on concept of friction of distance, which embodies, but goes beyond, an explanation for distance decay. Interaction between places is related to distance and interaction between more distant places requires more energy/higher cost (has greater friction).

(Anselin 1988).[10] Examples of models accounting for various types of spatial clustering include spatial lag models (the endogenous variable is spatially dependent), spatial cross-regression models (the exogenous variables are spatially dependent), and spatial error models (the error terms are spatially dependent) (LeSage and Pace 2009). Most applications are based on linear regressions, but spatial discrete choice models have also been applied (McMillen 1992; Pinkse and Slade 1998; Anselin 2002; Fleming 2004; LeSage and Smith 2004; Klier and McMillen 2008; Smirnov 2010).

Spatial heterogeneity is present if the mean and/or covariance structure “drifts” over a mapped process. It is important to note that, unlike in the case of spatial dependence, no spatial interaction between observations is assumed in the process generating spatial heterogeneity. It thus rests on the assumption of the “intrinsic uniqueness of each location” (Anselin 1996, p.112). Observed spatial heterogeneity can be modeled using traditional econometrics with spatial variables, as discussed above. *Unobserved spatial heterogeneity*, in contrast, implies that heterogeneity is present but cannot be fully explained by observed variables. The source of unobserved heterogeneity can be either error variance differences (heteroskedasticity) or parameter differences across spatial units. A commonly applied approach to data of this type is allowing parameters to vary across spatial units (e.g., geographically weighted regression, spatial regimes). Such models can be applied to discrete choice data (Wang et al. 2011; Budziński et al. 2017) and count/interval data, but are thus far rarely used for SP data analysis.

3. Topics in the literature – Spatial variables

The majority of the spatial SP literature has used spatial variables and traditional

[10] For example, the omission of income from SP analysis can lead to apparent spatial clustering, as WTP is conditional on income and income varies spatially—this effect can be anticipated based on economic theory.

econometric techniques. These studies frequently rely on at least weak grounding in microeconomic theory to form and test *ex ante* hypotheses about spatial effects. That is, spatial variables are incorporated in much the same way other exogenous variables whose effects are at least partially informed by welfare theory. This section characterizes the literature in this area, with the discussion organized following the theoretical foundations discussed above.

3.1 Distance decay

3.1.1 Estimating distance effects

The effect of distance on WTP/WTA can be estimated for an empirical determination of the extent of the market or to characterize preference heterogeneity within the market. Investigating distance effects requires sampling respondents at different distances from the site or good of interest, although hypothetical distances or related spatial information may also be included directly within valuation scenarios (e.g., in the context of wind farms: Ladenburg and Dubgaard 2007; Meyerhoff et al. 2010; land use change: (Luisetti et al. 2011; Liekens et al. 2013; Badura et al. 2019, this issue); urban green space: Tu et al. 2016).[11] Distances can be represented categorically (e.g., distances calculated for geographic areas such as postal codes or electoral districts, for example using area centroids (e.g., Campbell et al. 2008, 2009; Rolfe and Windle 2012; Johnston and Ramachandran 2013).[12] or continuously. For the latter, distances are calculated for each respondent. Calculations can be based on geocoding individual respondent addresses or locations (Johnston et al. 2016; Moeltner et al. 2017), or on respondents self-locating on a map (e.g., Abildtrup et al. 2013;

[11] This permits an investigation of distance effects and associated spatial variation in WTP directly through experimental variation of distance, although scenario adjustment or rejection can occur if the presented distances are not viewed as realistic (see Cameron et al. 2011).

[12] For examples, see Bateman and Langford (1997), Hanley et al. (2003), Sutherland and Walsh (1985), and Rolfe and Windle (2012).

Jørgensen et al. 2013). Models are specified to allow utility to vary as a discrete or continuous function of distance. As noted in section 2.3, approaches include single-step models wherein distance is incorporated directly into an empirical bid or utility function, and two-step models wherein distance serves as an explanatory variable in a second stage regression of conditional (individual-specific) WTP.

The exact nature of the distance measure can vary. Considerations include whether distance is calculated as travel, Euclidean or geodesic distance, and the starting/ending points used to calculate these distances. For example, Schaafsma et al. (2013) and Jørgensen et al. (2013) use travel distance, while many other studies use Euclidean or geodesic distance.[13] Starting points for distance calculations are often obtained using information on respondents' place of residence, available at varying degrees of detail (e.g., postcode centroid; respondent-provided location; mailing address; location recorded by interviewer). End points are often defined as the nearest point within the affected geographic area, but can also be defined as the nearest (or other) access point (Holland and Johnston 2017). The latter may be applicable if the site is not universally accessible and thus requires use of specific access points (Nielsen et al. 2016). Perceived and actual travel distance can differ, and perceived conditions may be more relevant when seeking to model SP responses (Adamowicz et al. 1997).

Conditional on the particular distance measure chosen, model specifications may imply linear or non-linear distance decay. For the latter, quadratic (e.g., Hanley et al. 2003; León et al. 2016) and logarithmic (e.g., Pate and Loomis 1997; Bateman et al. 2000; Liekens

[13] Travel distance can be challenging to obtain and is arguably better suited to local and regional study contexts, especially if natural or man-made obstacles imply a substantial difference between travel and geodesic/Euclidean distance. Geodesic or Euclidean distances may be more appropriate for analysis when considering values where site access is not required to realize value, such as non-use value (De Valck et al. 2017; Holland and Johnston 2017).

et al. 2013) functional forms are common, and other distributions have been explored (Concu 2007, 2009). Distance decay patterns can also vary depending on aspects of model specification and estimation not directly related to the distance specification itself (León et al. 2016). Beyond statistical model fit, non-linear functional forms may be justified since visitation frequency is often found to decrease more rapidly at close proximity to a site. Hence, a linear functional form may overstate benefits at large distances (Loomis 2000). The distance function may also vary across characteristics of a good (Concu 2007, 2009).

3.1.2 Extent of the Market

The extent of the market, or economic jurisdiction, is defined as the distance from the site or resource where WTP drops to zero (Smith 1993; Morrison 2002; Bateman et al. 2006). This area "includes all individuals receiving the good's benefits" (Cornes and Sandler 1996), and is often unlikely to coincide with political jurisdictions or other *ad hoc* definitions such as the customer base of companies proposing projects (Loomis 2000; Bateman et al. 2000). Misrepresentations of the extent of the market can result in large differences in aggregate benefit estimates (Sutherland and Walsh 1985; Brown and Duffield 1995; Pate and Loomis 1997; Bateman and Langford 1997; Loomis 2000; Hanley et al. 2003; Bateman et al. 2006; Meyerhoff et al. 2014), such that "[d]efinitions of the extent of the market are probably more important to the values attributed to environmental resources as assets than any changes that might arise from refining our estimates of per unit values" (Smith 1993, p.21).

In some cases it may not be possible to identify unambiguous geographical limits on the extent of the market without additional assumptions (Morrison 2002). For example, WTP does not always decrease monotonically with distance (Pate and Loomis 1997; Concu 2009; Rolfe and Windle 2012; Johnston and Ramachandran 2013; Johnston et al. 2015; Lizin et al. 2016), and some functional forms imply that WTP approaches zero asymptotically. In other instances, WTP or WTA may be inelastic to changes in distance (even when the effect is statistically significant), such that the distance gradient itself does not define the extent of the market (e.g., Loomis 1996; Johnston et al. 2017a). Recent work also suggests that there may be directional heterogeneity in distance decay for some environmental goods, such that the use of a single, unidirectional distance decay relationship can misspecify market extent (Schaafsma et al. 2013; Logar and Brouwer 2018).

3.1.3 Variation in distance effects

The presence and extent of distance decay can vary according to factors such as the type of value considered, the type of good, socio-demographic characteristics of the population and scenario framing. For example, Logar and Brouwer (2018) find that distance decay differs between residents of urban and rural areas. Olsen et al. (2019), in this issue, find a discontinuity in distance decay caused by a barrier in the landscape. Swait et al. (2019), also in this issue, identify differences in distance effects related to antecedent volitions—the fundamental goals that motivate decision processes. Multiple studies confirm different distance decay patterns in use versus non-use (or user versus non-user) WTP. A common though not universal finding is that WTP decreases more rapidly (with distance) for use values than for non-use values (Hanley et al. 2003; Bateman et al. 2006; Schaafsma et al. 2012, 2013). Some studies find no distance decay in WTP dominated by non-use value (e.g., Payne et al. 2000; Bulte et al. 2005; Johnston et al. 2015). Others have found a lack of distance decay for both use and non-use WTP (Lizin et al. 2016).[14]

[14] The validity of above findings depends on an ability to estimate theoretically valid measures of use and non-use value. In general, welfare theory does not support the empirical decomposition of total WTP into well-defined use and non-use components, at least in an unambiguous manner (Cummings and Harrison 1995). However, various approximations have been applied in the literature, including the estimation of user and non-user WTP as a proxy for use and non-use values (Bateman and Langford 1997; Bateman et al. 2006;

Beginning with Sutherland and Walsh (1985), studies have found different distance effects for option values (compared to use or non-use values alone), or used option values as an explanation for empirical results. For example, Jørgensen et al. (2013) find stronger distance decay effects among non-users and explain this via the possibility of non-users becoming users following project implementation. Bateman et al. (2006) also reference the idea of non-users becoming users to explain why distance decay is found for non-user compensating surplus (WTP for gain: final quality > present quality), but not for non-user equivalent surplus (WTP to avoid loss: final quality = present quality). There is also some evidence that distance decay in non-use values may be less likely when the good is of national significance or iconic (Loomis 1996, 2000; Rolfe and Windle 2012; Johnston et al. 2015).

Distance effects can be sensitive to framing of the valuation scenario and the design of the valuation task. For example, studies such as Concu (2007), Johnston and Ramachandran (2014), Rolfe and Windle (2012) and Pate and Loomis (1997) find that distance effects (including magnitude and/or statistical significance) can vary across different goods or attributes. Schaafsma and Brouwer (2013) find a more pronounced distance decay effect when choice sets contain fewer alternatives. Decisions about the framing of the valuation scenario and attribute selection in choice experiments may therefore play an important role in determining how estimated benefits vary across distance from a valued site.

3.1.4 Heterogeneity across geographical scales and jurisdictions

A number of studies investigate WTP differences across different geographical scales or

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Johnston et al. 2005).

jurisdictions affected by environmental change, thereby considering distance-related effects in discrete terms (Morrison and Bennett 2004; Johnston and Duke 2009; Brouwer et al. 2010; Martin-Ortega et al. 2012; Dallimer et al. 2015; Interis and Petrolia 2016) or distinguishing continuous distance effects from discrete effects across institutional boundaries (Bakhtiari et al. 2018). In such cases, spatial heterogeneity is assumed to vary discretely across jurisdictional or otherwise defined boundaries, typically in relation to a respondent's place of residence. Investigated areas can be mutually exclusive on the same administrative or geographical level (e.g., counties, states or river basins), or can be nested (e.g., communities, counties, federal state). Differences such as these can be particularly relevant for benefit transfers across scales or jurisdictions (Morrison et al. 2002; Morrison and Bennett 2004; Johnston and Duke 2009; Bateman et al. 2011; Martin-Ortega et al. 2012).

Findings reflect similar theoretical expectations as those for continuous distance evaluations. For example, improvements implemented over smaller jurisdictions are more likely to have proximate effects than improvements of a similar scope or scale conducted over larger jurisdictions, and hence are associated with higher WTP (Johnston and Duke 2009). Residents may also have a greater sense of ownership or responsibility for changes taking place in one's 'own' jurisdiction (Hanley et al. 2003; Bateman et al. 2005, 2006), or differ in their perceptions of natural assets across regions (Jacobsen and Thorsen 2010). However, effects on WTP can differ depending on the magnitude of environmental change (Brouwer et al. 2010). Differences in current endowments and substitutes across jurisdictions may also help to explain observed differences in WTP (Interis and Petrolia 2016).

3.2 Spatial substitutes and complements

The SP literature has devoted considerable attention to the importance of substitutes and complements for survey design, data analysis, and the interpretation and validity of results (e.g., Hoehn 1991; Arrow et al. 1993; Hoehn and Loomis 1993; Loomis et al. 1994; Carson et al. 1998; Whitehead and Blomquist 1999; Hailu et al. 2000; Carson 2012; Haab et al. 2013; Johnston et al. 2017b). The role of substitutes is also discussed in the literature addressing spatial dimensions of SP studies (Brouwer et al. 2010; Schaafsma et al. 2012; Jørgensen et al. 2013; Lizin et al. 2016; De Valck et al. 2017). For example, substitution effects play an important role in determining the extent of the market (Schaafsma et al. 2012, 2013; Jørgensen et al. 2013). In most cases, however, substitutes and complements have not been modeled formally, but rather have been stated as a potential explanation for observed spatial patterns. For example, Hanley et al. (2003) hypothesize that distance decay relationships are likely to vary spatially as a function of heterogeneity in substitute availability, mirroring similar arguments made regarding non-use values by multiple studies (e.g., Pate and Loomis 1997; Rolfe et al. 2002; Bateman et al. 2006).

Studies that have specifically analyzed the impact of substitutes and complements have generally found empirical evidence in support of these arguments. Pate and Loomis (1997), for example, find that variables capturing presence of substitutes can have a negative and significant effect on WTP in addition to the effects of distance. Bateman and Langford (1997) compare several studies in terms of their (subjectively rated) availability of substitutes and conclude that, for both user and non-user studies, lower WTP is associated with the presence of many substitutes. Recent SP studies (Schaafsma et al. 2012, 2013; Jørgensen et al. 2013; Brouwer and Schaafsma 2018; Logar and Brouwer 2018) and meta-analyses (Johnston et al. 2017a, 2018) consider the effect of substitutes in addition to other spatial factors such as distance. Studies such as these typically confirm that assuming a linearly expanding consideration set with distance falls short of the complexity of spatial patterns induced through the spatial arrangement of substitutes. For example, significant effects of substitutes can imply directional heterogeneity in WTP (Schaafsma et al. 2012, 2013; Logar and Brouwer 2018).

In some cases, substitute availability is modeled based on choices across multiple sites or choice alternatives. Multiple sites can be included as alternatives in labelled choice experiments (e.g., Schaafsma et al. 2012, 2013; Schaafsma and Brouwer 2013; Lizin et al. 2016; Logar and Brouwer 2018) or as choice attributes (e.g., Horne et al. 2005; Brouwer et al. 2010; Meyerhoff et al. 2014). However, the potential for such approaches to be susceptible to strategic behavior requires further study (Logar and Brouwer 2018). As noted by Schaafsma et al. (2013) and Schaafsma and Brouwer (2013), there are limits to the number of substitutes that can be included and trade-offs with task complexity should be considered.

Spatially varying substitutes—understood as sites or areas that provide either partial or full substitution for services affected by a policy change—may be identified using criteria defined by researchers, respondents, or both. Researcher-based definitions refer to different notions of 'similarity' to a valued site based on, for example, appearance, functionality or other dimensions. Substitute definitions may be area-based (e.g., Pate and Loomis 1997; Nielsen et al. 2016; De Valck et al. 2017) or site-based (e.g., number of sites within certain distance; distance or travel time to closest similar site Jørgensen et al. 2013). In addition, selection of suitable substitutes may entail aspects of site quality (e.g., natural versus managed forest; suitability of site for specific types of activity relevant to valued site). Respondent-defined consideration sets, for example based on past visitation (e.g., Peters et al. 1995), may be more reliable if substitutes are primarily understood as "competing destinations" (De Valck et al. 2017) rather than as sites providing a range of direct use, indirect use and non-use values. Further complications may arise if individual perceptions of substitutes are affected by the policy under consideration. Findings such as these highlight the challenges of identifying substitutes for consideration in the analysis; identification of individually relevant substitutes remains a challenge for all SP analysis (Johnston et al. 2017b).

3.3 Spatial scope and diminishing marginal utility

3.3.1 Spatial scope

Despite the focus in the literature on various types of discrete and continuous distance effects, there is an increasing recognition that spatial welfare patterns are likely more complex. Some recent work uses spatial variables that deviate from traditional distance-to-nearest-point measures to describe the quantity of an affected resource within a certain distance from a respondent's place of residence (i.e., quantity-within-distance).[15] Measures such as these are commonly used in revealed preference studies (e.g., Geoghegan et al. 1997; Paterson and Boyle 2002; Bateman et al. 2002) and are of particular importance for valuation of environmental change that affects areas rather than individual sites or points (Holland and Johnston 2017). The effect of these measures on welfare may be interpreted with regard to *spatial scope effects*—increasing benefits are accrued by respondents living in proximity of a greater area of a resource improved by a policy change (Yao et al. 2014; Holland and Johnston 2017).[16] In related work, Lanz and Provins (2013) find that WTP

[15] Similar measures have been used to quantify substitute availability (e.g., Nielsen et al. 2016).

[16] Distances over which areas of affected resources are estimated may be defined in various ways (e.g., Yao et al. 2014; Nielsen et al. 2016; Czajkowski et al. 2017), including estimation of 'optimal' distance bands for the calculation of relevant quantities (Holland and Johnston 2017).

increases when improvements are concentrated in close proximity to the respondents' place of residence. Other studies have defined spatial scope in terms of environmental changes that occur over different geographical extents. For example, a specified percentage of marine waters zoned as sanctuaries implies a different spatial scope if applied to regions with different total amount of marine waters (Spencer-Cotton et al. 2018).

3.3.2 Diminishing marginal utility

There is often spatial variation in the endowment of a good that characterizes the status quo prior to policy implementation (Bateman 2009; Glenk 2011). This is similar to a density perspective on substitute availability (De Valck et al. 2017), the primary difference being that the quality or quantity of the valued good itself is subject to spatial variation that leads to respondent-specific reference points. Because these reference points vary across space, expectations of diminishing marginal utility suggest that WTP/WTA estimates will differ across space. At least two types of applications address patterns of this type. The first concerns large sites or areas with spatially heterogeneous characteristics, for example large water bodies wherein baseline quality differs. Here, the quality characteristics of areas within these sites that are closest to a respondent's place of residence can affect WTP (Moore et al. 2011; Tait et al. 2012).[17]

A second type of application concerns the effect of respondent-specific endowments of land use or environmental quality, for example the endowment of a particular land use in specific distance bands around place of residence. The expectation is that greater endowments of the good in question result in lower marginal WTP for additional units of the good, as demonstrated for forest changes by Sagebiel et al. (2017), Czajkowski et al. (2017)

[17] Specifically, better quality of the site in proximity of one's home results in lower WTP for an additional unit of improvement.

and Varela et al. (2018),[18] and for water quality by Bateman (2009) and the meta-analyses of Johnston et al. (2017, 2018). Both types of applications assume congruence between objectively measured or researcher-defined quality and quantity characteristics and respondent perceptions. This congruence can be promoted via virtual reality techniques (Bateman et al. 2009; Matthews et al. 2017).

Distinctions between welfare patterns caused by spatial scope and diminishing marginal utility can be subtle, and the two effects can occur simultaneously. Variations in spatial scope typically occur when environmental quality changes are made to areas of different sizes—for example a water quality change to two different lakes that vary in surface area. In contrast, variations due to diminishing marginal utility can occur when increases in the quantity or quality of an environmental good occur over different baselines of that good—for example a one-hectare increase in wetland area considered over two regions with different baseline endowments of wetland.

4. Topics in the literature – Spatial dependence and unobserved spatial heterogeneity

Methods in the spatial econometrics and geo-statistics literatures emphasize spatial dependence or heterogeneity that are assumed to be an irreducible and otherwise unobservable feature of the data as distributed over space (Anselin 1988, 2001, 2010; LeSage and Pace 2009). Spatial autocorrelation is the correlation among observations of a single variable strictly attributable to the proximity of those observations in geographic space (Fischer and Wang 2011). Positive/negative spatial autocorrelation indicates that values of near-by observations tend to be more similar/dissimilar than values of

[18] A related concept is that of *cumulative spatial effects*. Knapp and Ladenburg (2015), for example, refer to cumulative effects with respect to wind energy developments as those wind turbines that people are cumulatively exposed to in a day. The study of Meyerhoff (2013) includes variables that were aimed to capture similar effects of cumulative exposure.

observations that are further apart. Based on this concept, several methods for various applications and stages of data analysis had been developed. These include tests for spatial autocorrelation such as Moran's I or Geary's C to detect spatial clustering of observations, and kriging as a method for prediction in geographical space.

Kriging includes a range of best linear unbiased predictor (BLUP) methods. It was initially developed to improve the precision of predictions of concentrations of gold and other metals in ore bodies, and is used, among many other areas, in mining, soil science, or for monitoring fish stocks. An important assumption underlying this approach is that the distance or direction between sample points reflects spatial correlation that can be used to explain variation across the surface; it uses complex weighted average techniques within a fixed or variable search radius.[19] Following our classification in Table 1, SP studies applying these methods rarely capitalize on strong foundations in microeconomic theory to characterize spatial welfare patterns. Although some of these studies are designed to evaluate prior hypotheses, many are exploratory in nature and seek to characterize spatial patterns of WTP or WTA that are unobservable using more traditional econometric approaches. Studies of this type are uncommon but increasing within the environmental stated preference literature.

Perhaps most similar to traditional observable-variable approaches are those that evaluate clustering across spatial regions defined in different ways. Franceschinis et al. (2016), for example, group municipalities according to altitude, income, and population categories. The authors then investigate to what extent the standard deviation of the random parameters varies across these defined areas. Individual-specific WTP estimates (averaged over municipalities) are subsequently used to develop WTP maps and kernel

[19] For these and other methods in spatial econometrics and geo-statistics, see contributions in Fischer and Getis (2010) and Fischer and Wang (2011).

density distributions.

Other studies have adapted methods from the spatial econometrics literature to evaluate local and global spatial associations in SP estimates, grounded in spatial autocorrelation. Campbell et al. (2008), the first study of this type, provide evidence of global clustering in WTP and analyze the sensitivity of resulting patterns to different definitions of the spatial weights matrix. Johnston and Ramachandran (2014), in contrast, propose methods to identify and evaluate local WTP hot (or cold) spots using local indicators of spatial association (LISAs). Meyerhoff (2013) and Johnston et al. (2015) find evidence for both global and local clustering. Johnston et al. (2015) also show that the number of hot and cold spots in WTP dominated by non-use values can vary depending on neighborhood definitions used to generate the spatial weights matrix. More recent examples include Czajkowski et al. (2017) and Rousseau et al. (2019), in this issue, both of whom evaluate spatial autocorrelation as part of a broader evaluation of spatial pattern.

Similar approaches may be used to interpolate and spatially predict values (preferences or WTP) for unsampled areas, based on geo-statistical interpolation methods (Burrough and McDonnell 1998; Anselin and Le Gallo 2006). Within SP valuation, these approaches typically seek to estimate values for unsampled spatial locations based on an interpolation of value estimates from surrounding sampled locations. As the first application of this type in the environmental SP literature, Campbell et al. (2009) apply kriging methods to interpolate and explore spatial heterogeneity in WTP. A similar approach is applied by Czajkowski et al. (2017). Johnston et al. (2015) apply an alternative spatial interpolator, inverse distance weighted (IDW) interpolation, to illustrate patterns in non-use WTP over a large geographical area. Research outside of the SP literature compares the properties and performance of different spatial interpolators and their suitability to different applications, including work in the hedonic pricing literature (e.g., Robinson and Metternicht 2006; Anselin and Le Gallo 2006). However, there is a lack of knowledge regarding the comparative performance of different spatial interpolators when applied to SP data.

In addition to the methods outlined above, a few recent studies have used different types of spatial regression models to evaluate patterns in individual-specific WTP estimates. Czajkowski et al. (2017), for example, use a spatial lag model to analyze spatial clustering in individual-specific WTP estimates from a choice experiment on forest management, with an inverse square function of distance used to create the spatial weights matrix. They also develop a spatially explicit latent class model to explore the spatial distribution of class membership. Using the same data, Budziński et al. (2017) investigate spatial clustering using a geographically weighted regression (GWR), which introduces space into the analysis via a "bandwidth parameter." GWR enables locally weighted regression coefficients to depart from their global values (Bivand et al. 2013). Despite reliance on the same data, Budziński et al. (2017) find spatial patterns in WTP estimates which differ from those reported in Czajkowski et al. (2017). Rousseau et al. (2019), in this issue, find little evidence of spatial patterns in WTP for transit attributes in a single urban area, contrasting to prior work in the literature which often finds significant spatial relationships. Differences such as these, combined with the strengths and weaknesses of various spatial econometrics models, suggest the need for additional research to evaluate the applicability and relevance of different types of spatial regression to welfare analysis, and the robustness of findings across these methods.

Although the majority of SP studies in the environmental valuation literature using spatial econometrics methods evaluate patterns in individual-specific WTP estimates that are generated by a first-step discrete choice model, related methods can be applied directly within a discrete choice model. Within the transportation literature, approaches such as the Generalized Spatially Correlated Logit (GSCL) model have been applied to model unobserved causes of spatial correlation across choice alternatives (e.g., Guo and Bhat 2007; Bhat and Sener 2009; Sener et al. 2011).

In concluding this section, it is worth emphasizing that it is often difficult or impossible to empirically distinguish unobserved spatial heterogeneity from spatial dependence. Both result in spatially varying parameter estimates and are indicated by spatial autocorrelation. This is an ongoing challenge for all models of this type, including those in the SP literature.

5. Survey design, sampling and response

The above sections focus primarily on theory and empirical analysis, once the data are available. However, WTP estimates may be further influenced by spatial variations in awareness, knowledge and experience, including spatial information provided intentionally or unintentionally by the survey instrument, and how this information is understood (or not) by respondents (Johnston et al. 2002, 2016; Glenk and Martin-Ortega 2018). Hence, spatial dimensions are also relevant to SP survey design and sampling, among other related methodological topics. Although topics such as these have garnered less attention in the literature than spatial theory and data analysis, they are nonetheless relevant to the validity and reliability of SP studies. Some SP-specific survey design aspects with direct relevance to spatial dimensions include the measurement and communication of distance in surveys; the provision of information on the spatial aspects of hypothetical policy scenarios and the location of respondents; the use of distance as attributes in choice experiments; and the inclusion of choice alternatives representing multiple sites to investigate spatial substitution patterns. Here, we give particular emphasis to two specific issues addressed by the literature. The first is the relevance of spatial information for survey design and scenario framing. The second is the impact of spatial dimensions on survey response propensities.

As noted by Johnston et al. (2017b, p. 326), valid SP welfare estimation requires "[t]he baseline (or status quo) condition(s), as well as the proposed change(s) relative to the baseline, [to be] be described in a way that … enables respondents to anticipate accurately the likely effects on their welfare." They also note on p.328 that "information required to describe the baseline and change may involve spatial […] features […] so that subjects understand the valuation scenario and its relevance" (see, e.g., Johnston et al. 2002, 2016; Roe et al. 2004; Horne et al. 2005; Bateman et al. 2005; Bateman 2009; Liekens et al. 2013; Badura et al. 2019, this issue). Welfare estimates emerging from SP value elicitation—like those emerging from revealed preference estimation—are often conditional on the spatial information available to individuals (Johnston et al. 2002). It is common practice to illustrate spatial aspects of policy scenarios using maps and graphics. These illustrate features such as affected watersheds or regions (e.g., Martin-Ortega et al. 2012), water bodies (e.g., Hanley et al. 2003; Bateman 2009; Johnston et al. 2012; Schaafsma et al. 2012; Jørgensen et al. 2013), recreation sites (e.g., Abildtrup et al. 2013), conservation areas (e.g., Horne et al. 2005), or the spatial layout of land use/cover changes (e.g., Johnston et al. 2002; Roe et al. 2004; Liekens et al. 2013). However, recent evidence suggests that respondents may have difficulty self-locating on such maps, and that additional personalized spatial information may be required to ensure valid welfare estimation (Johnston et al. 2016; Badura et al. 2019, this issue). Results such as these suggest that greater attention is required to how respondents understand and use spatial information presented in SP questionnaires.

A related and often overlooked issue is the topic of spatial sampling (Wang et al.

2012, 2013). Traditionally, most SP studies have relied on samples drawn randomly over a target population (i.e., probability sampling, with or without stratification) without regard to spatial dimensions. Assuming representative responses (i.e., absence of non-response bias, see below), correctly applied probability based sampling leads to unbiased parameter estimation under a wide range of conditions.[20] However, spatial data patterns that are overlooked during the design of sampling procedures can lead to systematic patterns in the data that—if unanticipated—cause bias and/or inefficiency in parameter estimation (Anselin 2001; Wang et al. 2012). These issues have received little attention within the SP literature. Hence, the practical relevance of applying spatial sampling techniques for SP welfare analysis remains unknown.

The propensity to respond to a SP survey also can vary systematically over space, leading to the potential for spatially non-representative samples even in the presence of appropriate spatial sampling protocols. Ignoring spatial self-selection of this type can result in biased mean and aggregate welfare estimates, particularly if both WTP and propensity to respond are spatially heterogeneous (Bateman and Langford 1997; Bateman et al. 2006; Johnston et al. 2015; Johnston and Abdulrahman 2017). For example, Bateman et al. (2006) find survey participation to be inversely related to distance but positively related to socio-economic status. In contrast, Nielsen et al. (2016) find no evidence of sample-selection bias with respect to forest cover and distance. Johnston and Abdulrahman (2017) find self-selection associated with factors including distance to the coast, elevation and location in a designated flood zone. Spatial self-selection can also manifest in more subtle and complex ways. For example, the proportion of protest bids may vary systematically over space

[20] There may be occasions where it is desirable to sample specific individuals from a population of interest. For example, Vedel et al. (2015) focus their sampling on a small number of large forest owners, who represent 4% of the population of forest owners, but own 96% of the forest area in Denmark. Their results are thus useful for analysing the potential, in terms of area affected, for changes in forest management.

(Söderberg and Barton 2014). Identification and correction of spatial response patterns such as these can be crucial to obtaining unbiased and representative welfare estimates.

6. Summary and outlook

This article summarizes the literature on spatial dimensions of SP welfare elicitation and analysis. Although this literature varies widely in terms of methods and findings, at least four consensus themes have emerged: (1) preferences and WTP often vary over space; (2) this variation is often relevant to welfare and policy analysis; (3) spatial patterns are complex and often defy modeling using simple, unidirectional distance-based analysis that overlooks confounding factors; and (4) no single modeling approach stands out as dominant or preferable across all or most applications.

The literature also seems to agree on the relevance of microeconomic theory to guide model specification and as a lens through which to interpret results. However, studies struggle with a lack of theoretical guidance for some types of spatial dimensions—for example the lack of insight from theory on whether and how non-use WTP should vary over space, and what types of distance measures are most relevant when travel to a site is not required to realize welfare change. Furthermore, efforts to reference microeconomic welfare theory to explain spatial welfare patterns emerging from studies that rely on spatial econometrics and geo-statistical methods have thus far been met with limited success. In an attempt to classify the literature according to the econometric approach used and the strength of links to economic theory (Table 1), most studies available to date can therefore be assigned to the upper left and lower right fields of the classification matrix representing combinations of traditional econometrics and strong (or weak) links to theory and spatial econometrics/geo-statistics and weak (or no) links to economic theory.

In summary, over three decades of work in this area have generated a consensus that “space matters”, but how it matters (specifically) and the most effective ways to model spatial dimensions remain topics of continued discovery in the SP literature. Based this observation, the remainder of this article offers suggestions for areas in which further research would be informative. This is not a comprehensive list, but rather identifies key topics frequently noted within the literature addressing spatial dimensions of stated preferences.

First, research is required to develop microeconomic theory better able to explain and harmonize divergent findings across the spatial SP literature, and to determine when and how spatial patterns should be relevant for welfare analysis within particular contexts. This includes theory that reconciles traditional microeconomic welfare theory with the geographical theory that underpins much of the spatial econometrics literature. Ideally, new conceptual and theoretical frameworks will help provide guidance on issues that still confound the empirical literature—such as how to resolve and model the many interacting spatial dimensions that can influence WTP (e.g., distance, substitutes/complements, directionality, spatial scope, spatial dependence, unobserved spatial heterogeneity). The treatment of these issues is frequently piecemeal, *ad hoc* and/or proof of concept, with different methods and observations scattered across different areas of the literature.

Similarly, the modeling of spatially heterogeneous welfare effects as due to observable or unobservable factors varies across the literature. In some cases, spatial dependence and clustering can suggest the omission of a relevant observable variable from the deterministic component of a statistical model. Spatial econometricians, however, frequently argue that a large proportion of spatial clustering is due to inherently unobservable, dynamic spatial processes (Anselin 2001). Evidence in the SP literature provides evidence for both types of patterns, sometimes within the same study (e.g., Johnston and Ramachandran 2014). The SP literature would benefit from systematic consideration of these different perspectives. To what extent does economic theory suggest that spatially dependent welfare effects can (and should) be appropriately modeled using observable variables, versus approaches that allow for spatial variation due to unobservable factors? What does each approach imply for welfare estimation and policy analysis?

Another area for which additional research is warranted is spatial interpolation and prediction (e.g., of WTP estimates). This topic is given considerable attention in the spatial econometrics and geo-statistics literature, but has thus far only been discussed by a few works in the SP literature. Spatially interpolating quantities such as WTP over unsampled points (or areas) involves considerations and assumptions beyond those associated with the estimation of the underlying econometric model, including the treatment of observed and unobserved sources of spatial clustering (Zimmerman et al. 1999). A related set of concerns applies when analysts use spatially interpolated values as explanatory variables in econometric models (Anselin 2001). To the extent that exercises such as WTP estimation, aggregation and evaluation of the extent of the market require the use of spatial interpolation and prediction (either in dependent or independent model variables), the insights from this literature apply.

Further research is also required to better inform the development of SP surveys capable of communicating relevant spatial information. The limited amount of work in this area suggests that spatial information presented in SP survey scenarios is relevant to WTP (Johnston et al. 2002; Badura et al. 2019, this issue), but also that respondents can misinterpret or misunderstand this information (Johnston et al. 2016). A nascent body of research has explored the use of virtual reality techniques to enhance SP value elicitation

(Bateman et al. 2009; Matthews et al. 2017), but the extent to which such methods can assist with spatial data comprehension is as yet unknown. Also relatively unstudied is the extent to which survey non-response has spatial pattern, and the extent to which these patterns are relevant to welfare and policy analysis. This reflects a broader lack of attention to non-response biases in the SP literature (Johnston et al. 2017b). Aspects such as these that relate to spatial value elicitation and aggregation have been given less attention in the literature than parallel issues related to data analysis, but can have a greater practical impact on policy analysis (Morrison 2002; Bateman et al. 2006).

Another often-overlooked topic that influences the relevance and use of SP studies is spatial data reporting. Policy applications of SP results often require information regarding spatial patterns. Unless this information is reported, analysts using studies for subsequent analysis (e.g., via benefit transfer; Bateman et al. 2011; Schaafsma et al. 2012; Johnston et al. 2015) must apply either implicit or explicit assumptions regarding these patterns. The lack of adequate data reporting is established in the valuation literature (Loomis and Rosenberger 2006). At the same time, confidentiality concerns may preclude publishing raw spatial data, such as the exact geocoded locations of respondents. Given these observations and challenges, we encourage work towards consensus standards for spatial data reporting in SP studies, building on similar but more general recommendations of Johnston et al. (2017b) for SP methods in general.

Finally, we highlight a frontier issue for environmental valuation in general, but one that is perhaps particularly relevant for spatial dimensions of SP welfare evaluation. When viewed from a general equilibrium perspective, it is established that residential sorting—in which people choose residential locations based in part on their environmental preferences—can lead to spatial correlations between environmental amenities and public preferences (Timmins and Murdock 2007; Timmins and Schlenker 2009; Baerenklau et al. 2010; Czajkowski et al. 2017). Spatial sorting of this type can lead to differences between partial and general equilibrium welfare measures (Klaiber and Phaneuf 2010). SP methods, in contrast, provide partial equilibrium welfare measures; these are almost universally contingent upon households' current locations,[21] and do not account for the possibility that considered hypothetical scenarios, if enacted, could lead to changes in general equilibrium sorting. To our knowledge, there is no work in the environmental valuation literature that assesses, formally, the potential implications of general equilibrium sorting for spatial dimensions of partial equilibrium SP estimates, for example as applied to hedonic methods by Kuminoff and Pope (2014). This reflects a more general rift between partial and general equilibrium valuation approaches in the literature. To the extent that hypothetical SP scenarios present non-marginal changes that could, if enacted, cause non-trivial sorting, this is an important area for future consideration.

In closing, we note that many of the recent advances related to spatial dimensions of SP welfare evaluation have emerged via a hybridization of SP methods with techniques from outside the valuation literature. Many disciplines (e.g., regional and urban economics, geography, geo-statistics, ecology) have developed more sophisticated spatial models and techniques than those commonly applied in SP valuation. In other cases, interdisciplinary efforts have led to enhancements in the understanding of spatial effects that cross disciplinary boundaries, such as relationships between spatial dimensions of biophysical changes and attendant patterns in welfare estimates. We encourage continued exploration of these models and techniques, along with research to better reconcile these "borrowed" approaches with microeconomic welfare theory and methods for SP welfare evaluation.

[21] A few applications in the literature consider how households would choose over alternative residential locations (e.g., Roe et al. 2004), but these do not formally analyze sorting behavior.

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Tables

Table 1: A classification matrix: Spatial dimensions of stated preference analysis

		Link to Economic Theory		
		Strong	**Weak**	**None (purely exploratory)**
Econometric Approach	**Spatial Variables (Traditional Econometrics)**	Spatial variables, and their inclusion in utility/bid functions, are derived directly and formally from economic theory. Modelled spatial patterns are linked to economic theory in a formal manner.	Spatial variables, and their inclusion in utility/bid functions, reflect relationships predicted by economic theory. Modeled spatial patterns are expected to conform with/are evaluated in relation to economic theory, but not necessarily in a formal and structural manner.	Spatial variables, their inclusion in utility/bid functions, and modeled spatial patterns are not informed by economic theory.
	Spatial Dependence and Unobserved Spatial Heterogeneity (Spatial Econometrics)	Spatial econometric specification is derived directly from microeconomic theory (i.e., a structural model). There are clearly defined, theoretical, *ex-ante* expectations for modeled spatial patterns.	Spatial econometric specification is not derived directly from economic theory, but follows clear microeconomic reasoning. There are *ex ante* expectations for modeled spatial patterns.	Spatial econometric specification is idiosyncratic and unrelated to microeconomic reasoning and theory.